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Research Article

An Efficient Brain Tumor Detection Using Ensemble Learning

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ABSTRACT

Brain tumors are serious health condition which need to be timely diagnosed and treated to avoid undesirable happenings. Most cancer-related deaths worldwide are caused by brain tumors. For effective treatment and better patient outcome, brain tumors must be detected correctly at their early stage in magnetic resonance imaging (MRI). MRI images are widely used for the diagnosis of brain tumors. The literature shows some detection approaches using deep learning methods to detect brain tumors but they lag in performance. To overcome this issue, we have proposed an ensemble learning based model that integrates transfer learning-based models with convolutional neural network (CNN). The proposed model trained and evaluated using a standard brain tumor dataset consisting of 3000 brain MRI images and achieved high detection accuracy of 98% with a very low false positive rate. Thus the proposed methodology is quite useful in the detection of brain tumors. The proposed method can help radiologists to identify brain tumors precisely which in turn may result an earlier diagnosis and better patient treatment.

Keywords: Brain tumor, Convolutional Neural Network (CNN), Transfer Learning, Ensemble Learning, Magnetic Resonance Image (MRI), VGG-19, Inception V3.

1. Introduction

The brain, one of the most intricate organs in the human body, operates through the coordination of billions of cells. Brain tumors develop when there is an uncontrolled proliferation of cells, leading to the formation of an anomalous cluster of cells within or around the brain. This cluster of cells can disrupt the regular functions of the brain and harm healthy brain cells [1]. Worldwide, brain tumors are a major source of mortality and morbidity. A successful treatment and better patient outcomes depend on early detection and precise diagnosis. For the detection and diagnosis of brain tumors, magnetic resonance imaging (MRI) is a frequently used technique. MRI scan is a technique that relies on magnetic fields and radio frequency pulses within the water molecules found in the human body. In contrast, MRI is considered more effective than Computed Tomography (CT) scanning because CT scanning does not utilize radio frequency technology. The complexity and heterogeneity of brain tumors, make it difficult for radiologists to interpret MRI images accurately. As a result, there is growing interest in creating automated systems for the diagnosis and categorization of medical images of brain tumors using deep learning methods. Machine learning algorithms were found worthy to analyze medical images to determine the presence of a tumors [2, 3].

The literature depicts the use of advanced models of machine learning such as deep learning for the analysis of medical images. Deep learning method operates directly on raw pixels and learns features by itself. Hence deep learning approaches such as CNN have also been adapted for medical image analysis which is robust to noise and illumination variations [4]. CNNs are specifically intended to deal with a variety of 2D shapes and are thus widely employed in visual recognition, medical image analysis, image segmentation, natural language processing, and many more. The capability of automatically discovering essential features from the input without the need for human intervention makes it more powerful than a traditional network. Several variants of CNN exist in the area that includes visual geometry group (VGG), AlexNet, Xception, Inception, ResNet, etc. that can be used in various application domains according to their learning capabilities [5]. In the domain of medical image processing, convolutional neural networks (CNNs) usually performed well but it needs further improvement in terms of detection accuracy. CNN has been used by several researchers to detect brain tumors [2,6,9,13,18] and found useful. However, CNN faces three major limitations as follows:
(1) CNN model required a vast number of images for training, which is often difficult to obtain in the medical imaging field.
(2) Convolutional Neural Networks (CNN) perform remarkably well at classifying images but on another side, it suffered to classify images that have a slight tilt or rotation.
(3) On the small dataset CNN suffered from overfitting problem.

To overcome these limitations, the work has proposed a deep learning-based method for identifying brain tumors by utilizing transfer learning. Methods such as Inception-V3, VGG 19 and CNN are integrated together with ensemble learning which used majority voting protocol to predict the brain tumor. Ensemble Learning has shown improved performance in several image classification tasks. For conducting the experiments, Brain Tumor Image Segmentation Challenge dataset used which contains 3000 Brain MRI images in two folders named, train and test, including labels, yes and no, in both. Performance criterion used in this work are detection accuracy, precision, recall and F1-score which were used to assess the effectiveness of our proposed approach. The results of the proposed model compared with the existing work done in past to assess the effectiveness of the proposed method. This work detected several forms of brain tumors with improved accuracy. The remaining sections of this work have been organized as follows. The literature review of related work in deep learning-based brain tumor detection is presented in Section 2. Dataset discussed in Section 3. The proposed ensemble learning based methodology is detailed in Section 4. Performance measures and experimental setup are given in section 5. Results are discussed in Section 6. At the end, section 7 concludes the work.

2. Literature Review

Advancements in the field of medical image processing had shown a diverse range of research initiatives. The realm of medical image processing has evolved into a multidisciplinary domain, attracting scientists from various backgrounds, including computer vision and machine learning. Segmentation is an important step in medical image processing. Segmentation divides the image into different parts according to some specified criteria to locate and obtain the desired region of interest. Hence segmenting a region of interest (ROI) from an image is an intricate and high demand task. Specifically, the ambitious pursuit of isolating tumors within MRI brain images presents a formidable challenge. Researchers worldwide deeply engaged in this field, striving to achieve optimal ROI segmentation. Various divergent approaches have been explored, each offering a unique perspective on the problem. In contemporary times, neural network-based segmentation methods emerged as highly effective tools, consistently delivering notable results. The adoption of these models is steadily increasing, signifying a growing momentum in their utilization. Consequently, our exploration has encompassed an array of studies, with the objective of identifying the most efficient and cutting edge techniques that hold substantial relevance for our work.

In a research study conducted by Mohsen et. al. [1], they undertook the task of classifying a dataset comprising of 66 brain MRIs into four distinct categories: glioblastoma, sarcoma, mild tumors, and metastatic bronchogenic carcinoma tumors. Notably, they employed the Fuzzy C-means clustering technique to segment the brain MRI images into five distinct sections. Subsequently, they extracted relevant features from these segmented tumors using the discrete wavelet transform (DWT). To manage the high dimensionality of the extracted features, the researchers applied Principal Component Analysis (PCA) as a dimensionality reduction method. This process resulted in a reduced-feature vector that was then used as input for the Deep Neural Network (DNN) classification phase. The results indicated the effectiveness of deep learning in specified tumor categories. A novel approach was employed, involving a combined Convolutional Neural Network (CNN) classifier model to assess the presence of a brain tumor in patients [2]. Additionally, machine vision techniques were utilized to automate the process of cropping the patient's brain from MRI scans. Notably, they achieved overall accuracy of this approach surpassed the baseline criterion of 50%. However, there exists the potential for substantial improvement through the incorporation of more extensive training data or the exploration of alternative models and methodologies. Shree and Kumar presented a novel approach for the identification and categorization of brain tumors in MRI images [3]. Their research introduced several key components to enhance the accuracy of tumor detection and classification. They proposed a preprocessing step aimed at noise removal, image smoothening, and feature extraction. This involved a combination of techniques, including discrete wavelet transformation (DWT), textural analysis, and the use of Gray-Level Co-occurrence Matrix (GLCM) features. For the critical task of classifying and detecting brain tumors within MRI images, a Probabilistic Neural Network (PNN) classifier was deployed. The utilization of this classifier demonstrated remarkable effectiveness in distinguishing between normal and abnormal brain tissues in MRI images. Notably, the experimental results showcased the high performance of the proposed technique, achieving an impressive accuracy rate of approximately 95% on the DICOM dataset. Das et al. [6] employed Convolutional Neural Networks (CNN) as a pivotal component of their study. Their central objective revolved around creating a custom CNN model, designed specifically for the classification of brain tumors within T1-weighted contrast-enhanced MRI images. This study used dataset encompassing a total of 3064 images, which contains three distinct types of brain tumors: glioma, meningioma, and pituitary tumors. By employing their CNN model, the investigators attained a substantial testing accuracy of 94.39%, an average precision of 93.33%, and an average recall of 93%.

In this work by Byale et. al. [7], introduced an innovative approach that combines Gaussian Mixture Model (GMM) and Grey Level Co-occurrence Matrix (GLCM) within a machine learning framework. To classify the tumors as normal, benign, or malignant, the researchers employed a Neural Network (NN). This research showcases a technique for MRI image analysis, combining GMM, GLCM, and NN to achieve detection accuracy in tumor classification, particularly in the context of normal, benign, and malignant tumor differentiation. Yakub Bhanothu et. al. [8] put forth a framework for the Detection and Classification of Brain Tumors within MRI Images. Their system advocates the utilization of a rapid RCNN algorithm to identify tumor regions and subsequently classify them into three distinct categories: glioma, meningioma, and pituitary tumors. The foundational architecture of this method relies on the VGG-16 model. Nonetheless, it is crucial to recognize a notable limitation associated with their approach. At its optimal performance level, the proposed method exhibited the lowest accuracy in detecting pituitary tumors, achieving an accuracy rate of only 68%. A predictive model was designed to detect brain tumors using a deep learning approach [9]. The work involved the implementation of a custom CNN model, which was then compared to the performance of the pre-trained CNN model and VGG16, using a brain tumor detection dataset sourced from Kaggle. The results of this comparative analysis revealed that the custom CNN model achieved a testing accuracy of 80%. Conversely, the fine-tuned VGG16 model demonstrated higher performance, achieving an accuracy of 90% on the same dataset.

In a different work, Kumar and Kumar [10] utilized ensemble techniques for brain tumor segmentation and classification. Their approach involved combining neural networks, Extreme Learning Machines (ELM), and support vector machine classifiers within an ensemble framework. The experimental results demonstrated that this approach exhibited increased stability, speed, and accuracy. Remarkably, the proposed method achieved accuracy of 91.17%. Komal Sharma et al. [11] proposed a Brain Tumor Detection system based on Machine Learning Algorithms. The process begins with the acquisition of MRI brain images, which serve as input for the pre-processing stage. Within this stage, the researchers employed Canny edge detection to identify edges within the filtered images. Subsequently, they conducted Watershed segmentation to pinpoint the tumor's location within the brain image. To enable image classification, they extracted essential features using the Gray Level Co-occurrence Matrix. For the classification of MRI brain images into normal or abnormal categories, Machine Learning algorithms were utilized. To potentially enhance accuracy, it may be beneficial to expand the dataset and incorporate intensity-based features alongside the texture-based features. Authors developed a classification system for brain tumors utilizing shape features extracted from MRI images [12]. The process involved segmenting brain tumor images and extracting various shape features, such as the center of gravity, circularity ratio, rectangularity, convexity, and solidity of the tumor region. These shape features were then employed to classify tumors as either benign or malignant. Two machine learning algorithms, Support Vector Machine (SVM) and Random Forest, were used for this classification task. It's important to note that their approach had certain limitations. The highest achieved accuracy was 86.66% when employing the Random Forest algorithm.

Ranjeet Kaur et al. [13] proposed a system for the Localization and Classification of Brain Tumors using both Machine Learning and Deep Learning Techniques. For tumor pre-processing, the authors explored five different image processing techniques, each with its own set of advantages and disadvantages. These techniques included Adaptive Histogram Equalization (AHE), Median Filter, Adaptive Median Filter, Weiner Filter, and Gaussian Filter. To classify the images, the study employed several image classification techniques, which included Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Decision Tree (DT), and Support Vector Machine (SVM). These diverse techniques were applied to effectively localize and classify brain tumors in the images. Ari and Hanbay [14] introduced an innovative model for brain tumor detection, combining deep learning with extreme machine learning (ELM) and utilizing a local receptive field (ELM-LRF) approach. Their methodology begins with the input of tumor images into a CNN model, which effectively extracts relevant features from the images. The pooled features are then passed to the hidden layer of the ELM, followed by the classifier. The approach signifies the effectiveness of their proposed model in the task of brain tumor detection, marking a significant contribution to the field.

In genetic algorithm-based approach [15] in which is a metaheuristic optimization technique, in conjunction with a support vector machine used to perform the segmentation and classification of brain MRI images. The experimental outcomes demonstrated a high level of precision, with an accuracy of approximately 91%, in distinguishing between normal and abnormal brain tissues from the MRI images. Iram Shahzadi et al. [16] introduced a framework known as CNN-LSTM, which stands for a Cascaded Framework for Brain Tumor Classification. This approach was designed to classify 3D brain tumor MR images into High-Grade and Low-Grade Brain Tumors. The authors implemented a cascade of Convolutional Neural Networks (CNNs) combined with a Long Short-Term Memory (LSTM) Network. To achieve this classification task, the researchers utilized pretrained VGG-16 models to extract features, which were then fed into the LSTM network for the purpose of learning high-level feature representations. These representations were used to classify the 3D brain tumor volumes into either High-Grade or Low-Grade tumors. However, it's important to note a limitation of their approach: due to the limited amount of training data available, accurately predicting pixel labels for brain tumors became a challenging task. Devkota et al. [17] developed a segmentation process that relies on Mathematical Morphological Operations and a spatial Fuzzy C-Means (FCM) algorithm. This approach was aimed at enhancing computational efficiency. However, it's worth noting that the proposed solution had not undergone evaluation up to that point. According to the reported outcomes, the approach demonstrated promising results, with a cancer detection rate of 92% and a classifier accuracy of 86.6%. These findings suggest the potential effectiveness of their methodology, although further evaluation and testing would be necessary to validate its performance.

In a separate research study, Sajjad et. al. [18] proposed a model for brain tumor classification into four distinct stages. Their approach involves several key steps to enhance classification accuracy. To begin, the researchers employed a Convolutional Neural Network (CNN) model for image segmentation, effectively delineating the regions of interest in the brain images. Following segmentation, they employed an extensive data augmentation technique to augment the dataset, increasing its diversity and robustness. The augmented images were then inputted into a pre-trained CNN model, specifically VGG19, for feature extraction and classification. This approach demonstrated substantial promise, achieving an accuracy rate of 90.67% when tested on the radiopaedia dataset. Focusing on region-based fuzzy clustering and a deformable model, Rajendran et al. [19] achieved impressive results in their work. Specifically, they reported an accuracy of 95.3% for the Active Shape Model (ASM) and an 82.1% Jaccard Index based on an Enhanced Probabilistic Fuzzy C-Means model that incorporated various morphological operations. These outcomes highlight the effectiveness of their approach in the context of image segmentation. Hasnain Ali Shah et. al [20] introduced a robust approach for the detection of brain tumors in Magnetic Resonance Images (MRI) using a fine-tuned Efficient Net model. The core of their approach relies on transfer learning and fine-tuning techniques, which are deeply rooted in deep learning (DL) algorithms and encompass several hyper-parameters used for training and optimization. This method exhibited longer processing time, likely due to the complexity of the model and the training process. Moreover, the high accuracy was attained with a relatively small dataset, and there may be challenges when scaling to larger datasets, where the loss function might struggle to effectively minimize errors for a larger number of parameters. G. Hemanth et al. [21] presented a brain tumor detection system using a machine learning approach. Their work introduced an automatic segmentation method that relies on Convolutional Neural Networks (CNNs), specifically using small 3x3 kernels. CNN was employed to directly extract features from pixel images with minimal pre-processing, thus requiring fewer specific tasks compared to conventional methods while effectively capturing features. The limitation of their work is the reliance on neighbourhood pixels in brain tumor images.

Dina et al. [22] presented a model that utilized the Probabilistic Neural Network (PNN) model, which is associated with Learning Vector Quantization. Their study involved the evaluation of this model using a dataset consisting of 64 MRI images, with 18 MRI images designated for testing and the remainder used for training. To enhance the quality of the images, Gaussian filtering was applied. The noteworthy outcome of their work was a significant reduction in processing time, with the modified PNN method managing to reduce processing time by 79%. This achievement highlights the efficiency of their approach in image processing. Yantao et al. [23] employed a Histogram-based segmentation technique in their study. They approached brain tumor segmentation as a three-class problem, categorizing regions as tumor (including necrosis and tumor), edema, and normal tissue. This classification was performed using two modalities, FLAIR and T1. To identify abnormal regions, they employed a region-based active contour model on the FLAIR modality. Within these abnormal regions, they distinguished edema and tumor tissues using the contrast-enhanced T1 modality, utilizing the k-means method. Their approach achieved a Dice coefficient of 73.6% and a sensitivity of 90.3% for the segmentation task.

B. Kokila et al. [24] introduced a novel approach for Brain Tumor Detection employing Convolutional Neural Networks (CNN). They recognized that existing methods often involve different models for detection and classification, leading to increased computational complexity. In response to these challenges, their proposed method addresses these issues comprehensively. Their approach for diagnosing brain tumors encompasses both brain tumor classification and brain tumor identification modules. They reported overall accuracy of 92%, highlighting the effectiveness of their method in addressing these challenges and improving brain tumor diagnosis. This research offers a valuable contribution to the field of medical image analysis. Badran et al. [25] employed edge detection techniques, specifically the Canny edge detection model, in conjunction with adaptive thresholding to extract the Region of Interest (ROI). Their dataset consisted of 102 images, and they followed a multi-step process for analysis. Initially, the images underwent preprocessing. Subsequently, for two separate sets of neural networks, they applied different methods: Canny edge detection for the first set and adaptive thresholding for the second set. Afterward, they represented the segmented images using a level number and extracted characteristic features using the Harris method. Two neural networks were employed for the task: the first one aimed to detect whether the brain was healthy or contained a tumor, while the second one focused on identifying the specific tumor type. Upon analyzing and comparing the outcomes of these two models, it was evident that the Canny edge detection method produced superior results in terms of accuracy.

Sanjay Kumar et al. [26] introduced a method for Brain Tumor MRI Images Semantic Segmentation using Fully Convolutional Neural Networks (FCNN). Their approach aimed to enhance the effectiveness and accuracy of brain tumor detection by combining deep learning and machine learning techniques, particularly through 3D segmentation. In their methodology, FCNN was employed for tasks such as smoothing, enhancement, and segmentation of brain tumor MRI images. However, it's important to note a limitation of this approach: the transition from a Fully Convolutional Neural Network (FCNN) to a Convolutional (CONV) layer reduces the number of parameters, which can impact flexibility. While this limitation did not significantly affect the results in this paper due to a small dataset, it could have a more substantial impact in larger-scale applications. S. Beatrice et. al. [27] introduced an approach for brain tumor detection utilizing Convolutional Neural Networks (CNNs). Their proposed method commenced with a dataset consisting of 253 Brain MRI Images, categorized into two folders: "yes" and "no". To enhance the dataset and improve training, they employed data augmentation, a technique involving the generation of modified or synthetic data from the original dataset. This process led to the creation of a new dataset comprising 2065 images. Following data augmentation, image preprocessing was applied. In the final stage, a CNN model was applied to the preprocessed images, consisting of three essential layers: a Convolutional layer for feature extraction, a pooling layer for image enhancement, and a fully connected layer for image classification. To mitigate overfitting, L2 regularization was incorporated into all convolution layers, along with strategically placed batch normalization layers. The investigation yielded promising results, with a validation accuracy of 96% and a corresponding loss value of 0.3476. This research demonstrates the effectiveness of their CNN-based approach in accurately detecting brain tumors, offering a valuable contribution to the field of medical image analysis. Research study discussed above showed the limitations of the past proposed models for brain tumor detection. These limitations include model complexity, increased training time and less detection accuracy. Our proposed methodology overcomes these limitations.

3. Dataset

The work uses publicly available dataset sourced from Kaggle repository [28]. This dataset is comprised of 3000 MRI images of brain scans. Within the dataset, two distinct folders are present: "train" and "test," collectively containing a total of 3000 Brain MRI Images. In the train folder, the "yes" subfolder encompasses 1043 Brain MRI Images depicting various tumorous conditions, while the "no" subfolder contains 1057 Brain MRI Images presenting nontumorous cases. In the test folder, the "yes" subfolder contains 457 Brain MRI Images depicting tumorous conditions, while the "no" subfolder contains 443 Brain MRI Images presenting non-tumorous cases. Table 1 depicts the numbers of images present in various folders and subfolders available on Kaggle and figure 1 presents some MRI images of two categories. All the images were two-dimensional and had the common dimensions of 256x256 pixels. It's important to note that all images had undergone skull-stripping, and they were categorized as "yes" if they contained a tumor and "no" if they did not.

Table 1. Description of the dataset

Brain Tumor Data Set			
train folder		test folder	
Yes	No	Yes	No
1043	1057	457	443

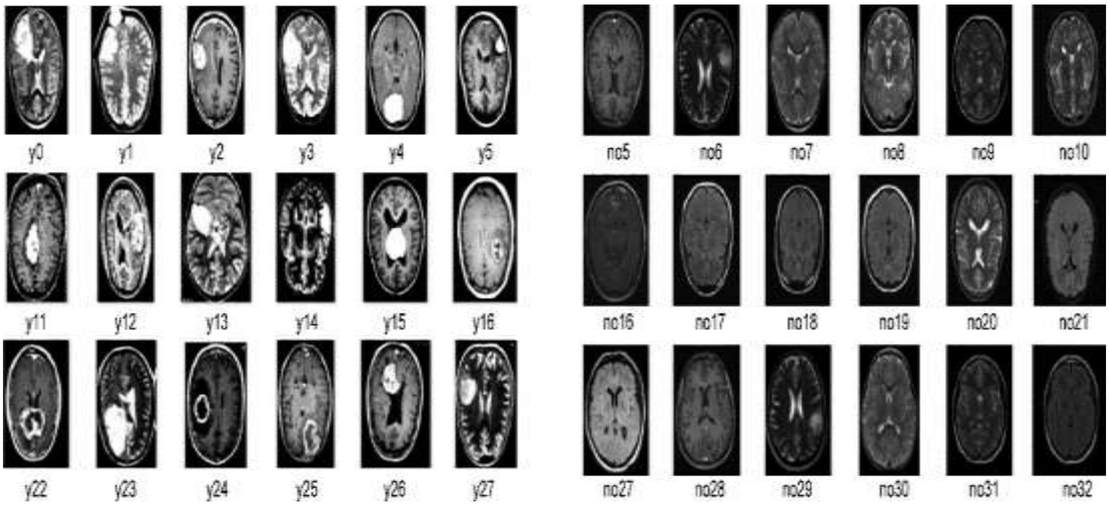

Fig 1. MRI images of two categories: y- with tumor and no-without tumor

The dataset consists of 3000 brain MRI images depicting both brain tumor and non-tumor conditions. All the images were two-dimensional and shared the common dimensions of 256x256 pixels. To prepare these images for neural network input, the dimensions of these images are transformed into 180 x 180 x 3 pixels. This pre-processed dataset, accompanied by corresponding labels, serves as the input for the neural network. In this context, a label of "0" signifies an image without a tumor, while a label of "1" signifies an image depicting the presence of a tumor.

4. Proposed Brain Tumor Detection Model

The work proposed an ensemble learning model that integrates CNN with VGG 19 and inception V3 to produce more accurate results. Ensemble learning is a strategy where multiple models are trained on the same dataset, and their predictions are amalgamated or combined. The primary goal of ensemble learning is to improve the performance by leveraging the combined knowledge of these models, surpassing the capabilities of any single model. To achieve this, careful consideration is required in terms of both the selection and construction of the individual models in the ensemble, as well as the optimal methods for merging their predictions. Our proposed methodology for brain tumor detection is shown below using block diagram in Figure 2.

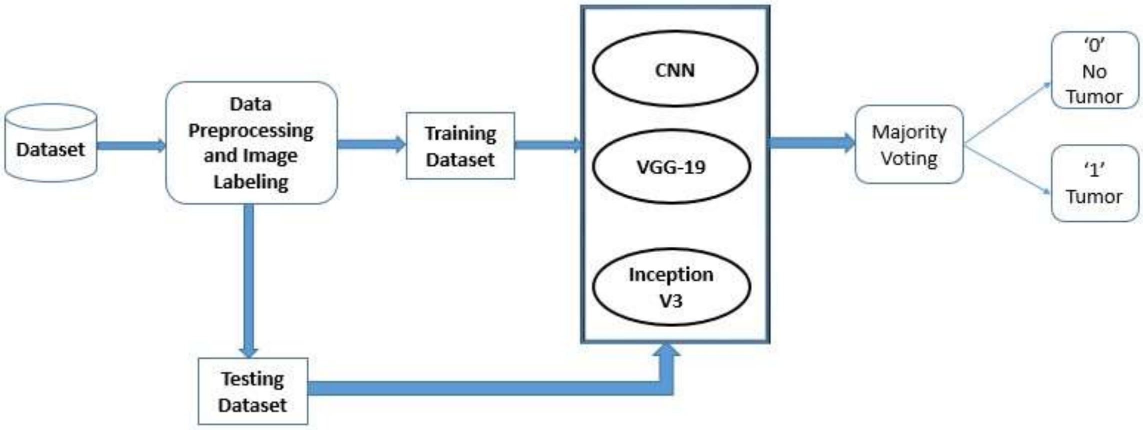

Fig 2. Proposed Methodology for brain tumor detection

The working of the model starts with image extraction and loading labels from the dataset. The extracted images are pre-processed before putting them into training and testing sets. The ensemble model integrating the CNN, VGG19 and Inception V3 trained with training dataset and majority voting method is used in this process. Finally, the testing dataset is applied on ensemble model to measure the performance of the proposed methodology. The proposed ensemble learning model combines the predictions of all 3 models i.e. CNN, InceptionV3 and VGG-19 using the Majority Voting Count technique. The processes of this technique are demonstrated in Figure 3. Majority voting count is a straightforward and effective way to combine the predictions of multiple classifiers to make a final decision. It is particularly valuable when individual models have different strengths and weaknesses, as the ensemble can compensate for the shortcomings of any single model and this technique often helps to enhance the overall accuracy and robustness of the ensemble in classification and detection tasks. In the majority voting count, each model's vote carries an equal weight, so all predictions are given the equal importance, or we can say all models have an equal share in the final decision. The class that receives the majority votes among the ensemble members is chosen as the final prediction for the input data point. If there's a tie or an equal number of votes for multiple classes, additional techniques such as breaking the tie through random selection or using weighted majority voting can be applied. In our case three models are used hence no such case predicted. The below pseudocode snippet shows the working of majority voting count.

Algorithm: majority_voting_count

1. ans= []
2. for i in range (0,900):
3. count=0
4. count=cnn_Y_pred[i]+vgg19_Y_pred[i]+inception_Y_pred[i]
5. if(count>=2):
6.   ans.append(1)
7. else:
8.   ans.append(0)

Ensemble learning, start by training multiple base models on the same dataset. In this work we trained CNN, VGG 19 and Inception V3. Each model produces its own set of predictions for a given input. New data points pass through each of the individual models in the ensemble for prediction and each model independently predicts a class label. Thereafter, count the number of votes for each predicted class by individual models across the ensemble.

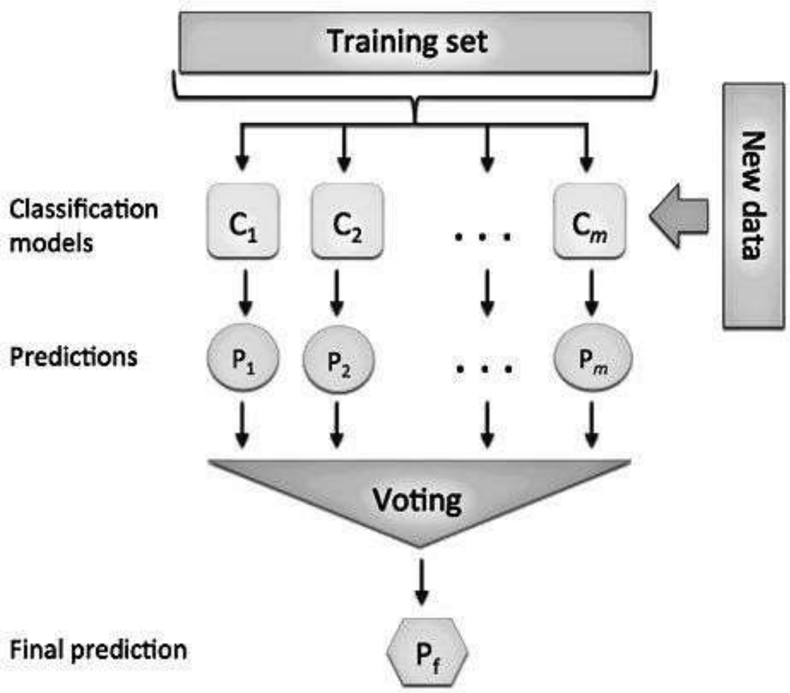

Fig 3. Majority Voting Count process

Description of CNN, VGG-19 and Inception-V3 used in our proposed methodology provided below in this section.

4.1 8-layer Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a variant of a feed-forward Artificial Neural Network (ANN) characterized by its neural connectivity pattern which draws inspiration from the structure of neurons in the visual cortex of animals. CNN faced a drawback of overfitting on small dataset[29].

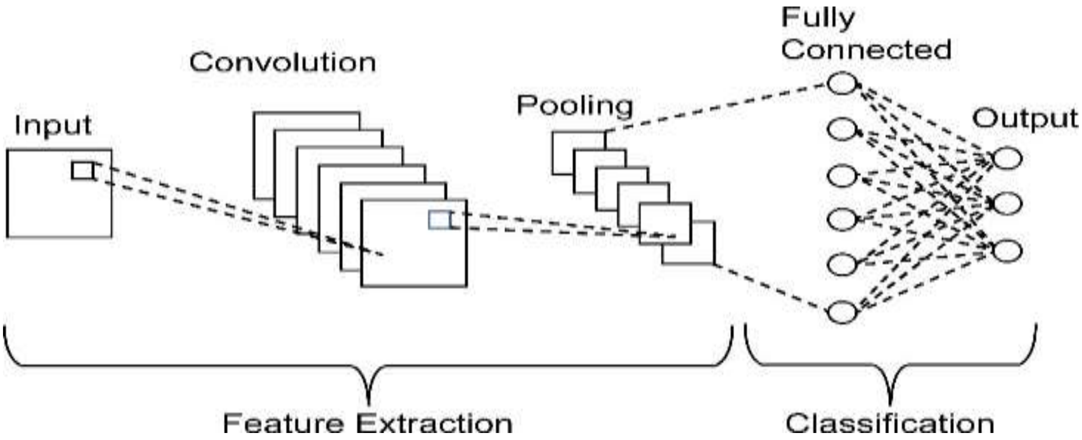

Fig 4. CNN Architecture

Figure 4 shows the general architecture of CNN which is configured as per the nature of the problem in hand. Figure 5 below presents the proposed "8-layers CNN" architecture used to classify the tumors. It is a mathematical method that performs a dot product between two matrices to construct a transformed feature map. One matrix relates to the kernel, while the other presents the pixel intensity values of the original image. The kernel is used to move vertically and horizontally over the original image to extract properties such as borders, corners, shapes, etc. In the proposed architecture, we take MRI slices as input, process the slices in different layers, and differentiate them from one another.

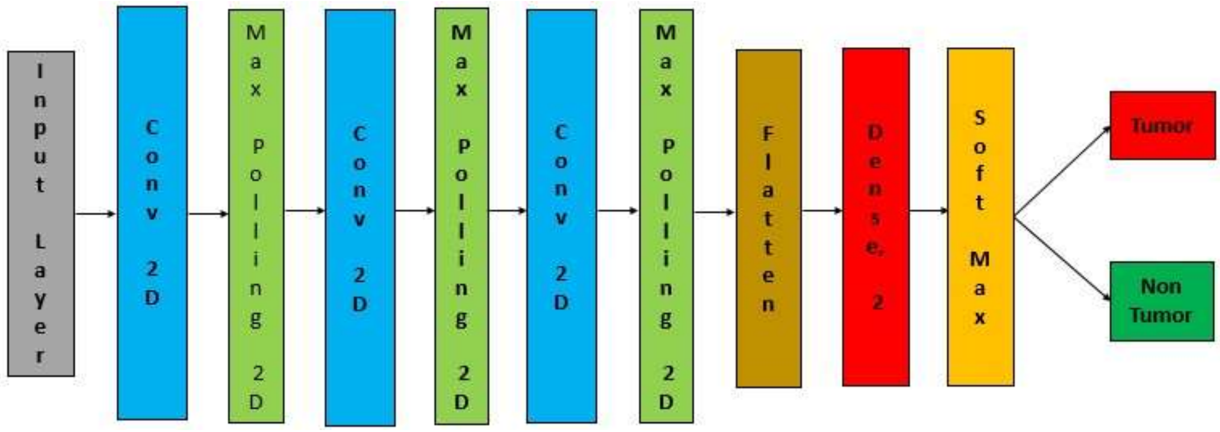

Fig 5. Proposed 8-layers CNN architecture

In this work, a total of 8 layers are used to process the slice. When we move further into the model, it begins to find better features like blurring, sharpening, texturing, and gradients direction. A total of three convolutional layers with kernel sizes, 3×3 are included in the '8-layers CNN" architecture. We move the filter 1 pixels at a time using stride one over the input matrix. For padding, we preserve the original size of the image by applying zero paddings, to avoid losing the details of the image. The following equation describes the convolutional layer:

$$C(h,d) = (k * f)(h,d) = \sum_i \sum_j k(h-i, d-j) f(i,j)$$

where, k is the image with a size of (h, d), and (i, j) corresponds to the kernel size value with a f-number of filters. As an activation function, we used the Rectified Linear Unit (ReLU) which performs non-linear operations within the convolutional layer. The ReLU activation function helps to solve the gradient vanishing problem using the backpropagation process. The ReLU is defined as follows:

$$F(z)=\max(0, z)$$

The ReLU activation function is graphically presented in Figure 6. In each of the next levels, pooling layers help to minimize the dimension of the transformed feature map. In this architecture, a total of 3 pooling layers are used. Different pooling layers are available in the CNN model, including max pooling, min pooling, and average pooling. We choose max pooling with size of the pool, 3×3 to retrieve the most prominent features from the transformed feature map. Figure 7 illustrates the max-pooling procedures where the feature map is in 4×4 blocks. Max-pooling generates the most dominant features in every 2×2 blocks. Figure 8 illustrates the convolutional approach to generate the feature map.

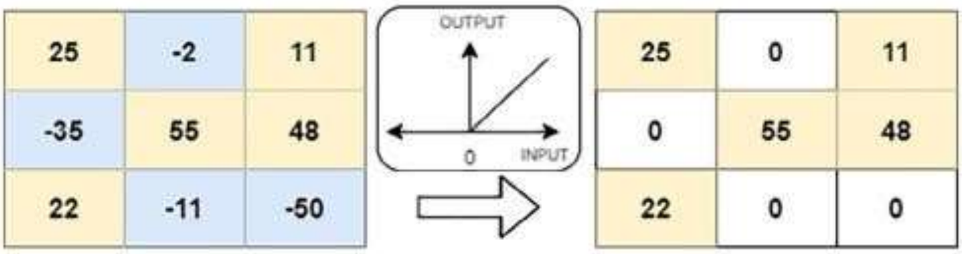

Fig 6. ReLU operation

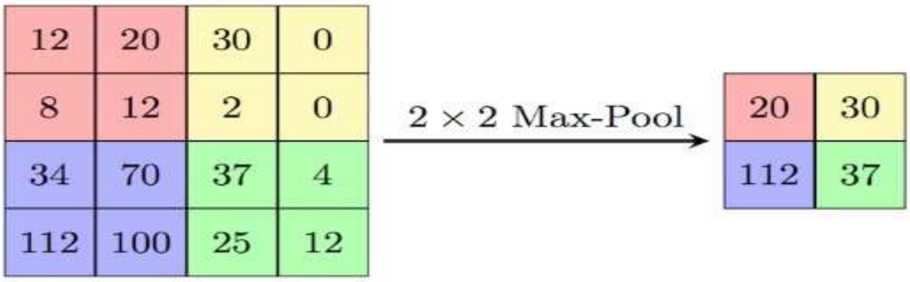

Fig 7. Max-Pooling procedures

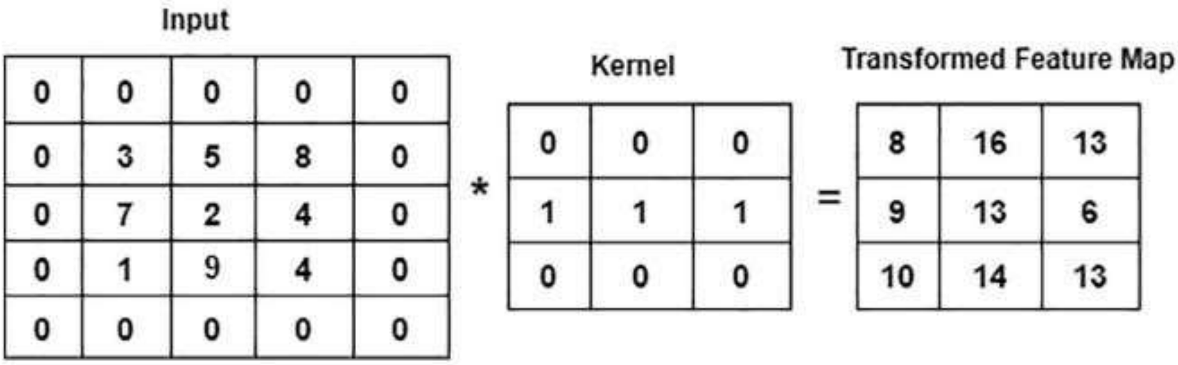

Fig 8. A sample Convolution operation on 5x5 image using 3×3 kernel

We have used SoftMax function as our activation function in the output layer of our proposed model, which predicts a multinomial probability where the probabilities of each value are proportional to the relative scale of each value in the vector. In the softmax activation function, the outcome value is between 0 and 1 which is defined as follows:

$$\text{softmax}(z)_j = \frac{\exp(z_j)}{\sum_{i=1}^{n} \exp(x_i)}$$

4.2 Transfer Learning based models

Transfer learning does well when the volume of data is limited since such a model is previously trained on a large dataset (e.g., the ImageNet database), containing millions of images. In this approach, the pre-trained model with adjusted weights is adopted for the classification tasks. Another benefit is that it does not require a massive number of computational resources since the model data is limited. In this approach [30] used a pre trained ResNet34 model to detect normal and abnormal brain MRI images. Inspiring from this, we have used two pre-trained models VGG-19 and Inception-V3.

4.2.1 VGG-19

It stands for Visual Geometry Group 19-layer model, is a well-known convolutional neural network (CNN) architecture in the field of deep learning. It was developed by the Visual Geometry Group at the University of Oxford. VGG-19 is distinguished by its deep structure, comprising 19 weight layers. The model architecture, primarily featuring 3x3 convolutional layers and 2x2 max-pooling layers. These components work in tandem to extract features from input images. VGG-19 has consistently delivered outstanding performance in image recognition and classification tasks, setting benchmarks in various computer vision challenges. Its straightforward design and proven accuracy have made it a popular choice in numerous deep learning applications and research projects. The proposed VGG-19 architecture is shown in Figure 9.

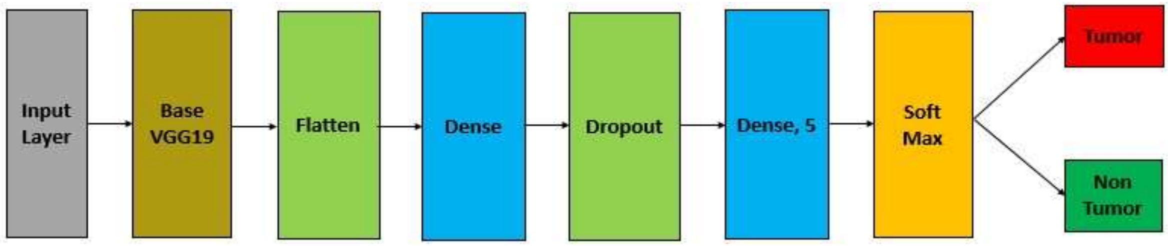

Fig 9. VGG 19 with dense layer

We have added 8-layer Artificial Neural Network (ANN) architecture in pre-existing VGG-19 model. The objective of this addition is to capture subtle nuances in brain images that might be indicative of tumor presence. Simultaneously, we have freeze the weights of the VGG-19 model. By freezing the weights, we preserve the knowledge encoded in these layers and avoid overfitting on the limited data for specific task. Here we have used 6-dense layers. In all dense layers, the ReLU activation function is used. A dropout layer which is placed between two dense layers is also used to overcome the over-fitting problem. Finally, this modified VGG 19 architecture is used for detection of brain tumor.

4.2.2. Inception-V3

Inception-V3 is a deep neural network architecture featuring a total of 48 inception layers. Each inception layer comprises four convolutional layers, each followed by activation functions, along with two max-pooling layers. Consequently, the entire architecture is composed of a grand total of 311 convolutional layers. The proposed InceptionV3 architecture is shown in Figure 10.

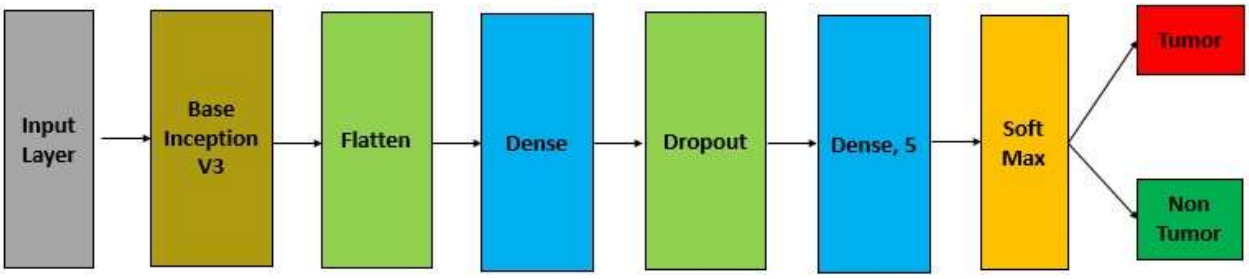

Fig 10. Inception V3 with dense layers

In our proposed Inception-V3 architecture we added 8-layer ANN architecture in pre-existing model. This addition aims to capture subtle nuances in brain images that might be indicative of tumor presence. Simultaneously, we freeze the weights of the Inception V3 model. By freezing these weights, we preserve the knowledge encoded in these layers and avoid overfitting on the limited data for specific task. Here we have used 6-dense layers. In all dense layers, the ReLU activation function is used. A dropout layer which is placed between two dense layers is also used to overcome the over-fitting problem. Finally, this modified Inception-V3 architecture is used for detection of brain tumor.

5. Performance Measures

To assess the model's performance, the work has employed the several metrics. To evaluate the performance of proposed architectures we used different evaluation metrics including accuracy, precision, recall, false positive rate (FPR), true negative rate (TNR), and F1-score. Accuracy is defined as the fraction of correctly classified images or samples divided by the total number of images in the dataset. These metrics are calculated as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{FPR} = \frac{FP}{TN + FP}$$

$$F1 - score = \frac{2 \text{ x } recall \text{ x } precision}{recall + precision}$$

Where, TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives.

5.1 Platform and Parameters

The proposed method was implemented using Python and Keras and TensorFlow serving as the backend. The training process of all the models are tuned with hyper-parameters which are mentioned in Table 2. The choice of parameters is made on measure of performance improvement, and it is depicted in Table 2.

Table 2. Choice of model parameters

Model	Hyper-parameter	Choice of parameters
CNN, VGG 19 and Inception V3	Loss function	Sparse Categorical Cross
	Optimizer	Adam
	Metrics	accuracy
	Epochs	40
	Batch_size	32
	Learning_rate	0.01

6. Results and Discussion

This section presents the results and discusses them. Section 6 has 4 subsections. Subsection 6.1 discusses the results of CNN and subsection 6.2 discusses the results of Inception V3. Subsection 6.3 talks about the results of VGG-19. Afterwards, subsection 6.4 presents the results of the proposed ensemble learning model discussed earlier. At the end, subsection 6.5 compares the performance of the proposed ensemble learning model with existing work done in past.

6.1 Results of CNN

CNN architecture was trained for 80 epochs with a batch size of 32 using sparse categorical cross-entropy as the loss function. The Adam optimizer with a very low learning rate of 0.01 was used to optimize the training. Few epochs of CNN presented in figure 11. The confusion matrix produced after 80 epochs is shown in figure 12 below.

```
Epoch 1/80
66/66 [==============================] - 2s 28ms/step - loss: 0.5923 - accuracy: 0.6944 - val_loss: 0.4961 - val_accuracy: 0.7856
Epoch 2/80
66/66 [==============================] - 2s 25ms/step - loss: 0.4421 - accuracy: 0.8151 - val_loss: 0.3951 - val_accuracy: 0.8222
Epoch 3/80
66/66 [==============================] - 2s 24ms/step - loss: 0.3324 - accuracy: 0.8637 - val_loss: 0.3142 - val_accuracy: 0.8589
Epoch 4/80
66/66 [==============================] - 2s 24ms/step - loss: 0.2617 - accuracy: 0.8963 - val_loss: 0.2353 - val_accuracy: 0.8967
Epoch 5/80
66/66 [==============================] - 2s 24ms/step - loss: 0.1928 - accuracy: 0.9347 - val_loss: 0.2052 - val_accuracy: 0.9200
Epoch 6/80
66/66 [==============================] - 2s 25ms/step - loss: 0.1408 - accuracy: 0.9502 - val_loss: 0.1654 - val_accuracy: 0.9378
Epoch 7/80
66/66 [==============================] - 2s 25ms/step - loss: 0.1300 - accuracy: 0.9568 - val_loss: 0.1660 - val_accuracy: 0.9500
Epoch 8/80
66/66 [==============================] - 2s 25ms/step - loss: 0.1066 - accuracy: 0.9584 - val_loss: 0.1172 - val_accuracy: 0.9600
Epoch 9/80
66/66 [==============================] - 2s 25ms/step - loss: 0.0846 - accuracy: 0.9700 - val_loss: 0.1513 - val_accuracy: 0.9600
Epoch 10/80
66/66 [==============================] - 2s 25ms/step - loss: 0.0657 - accuracy: 0.9769 - val_loss: 0.1159 - val_accuracy: 0.9700
```

Fig 11. Sample epochs: CNN

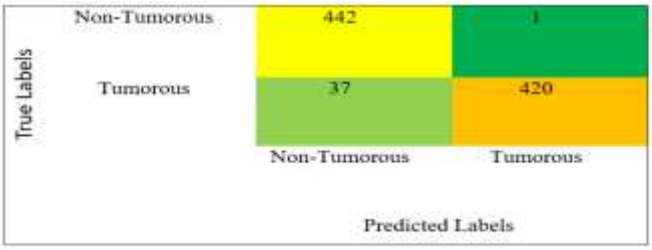

Fig 12. Confusion Matrix CNN

Table 3. Performance of CNN

TP	TN	FP	FN	Precision	Recall	FPR	F1 Score
420	442	1	37	99.67	91.90	0.22	0.95

The performance of CNN is depicted in table 3.

6.2 Results of Inception V3

Inception V3, a deep CNN architecture was trained for 80 epochs with a batch size of 32 using sparse categorical cross-entropy as the loss function. The Adam optimizer with a very low learning rate of 0.01 was used to optimize the training. Few epochs are presented in figure 13. The confusion matrix produced after 80 epochs is shown in figure 14 below.

```
Epoch 1/80
66/66 [==============================] - 9s 73ms/step - loss: 0.7893 - accuracy: 0.4993 - val_loss: 0.6889 - val_accuracy: 0.7522
Epoch 2/80
66/66 [==============================] - 3s 51ms/step - loss: 0.6507 - accuracy: 0.6467 - val_loss: 0.4921 - val_accuracy: 0.8000
Epoch 3/80
66/66 [==============================] - 3s 51ms/step - loss: 0.4771 - accuracy: 0.8624 - val_loss: 0.3896 - val_accuracy: 0.9211
Epoch 4/80
66/66 [==============================] - 3s 51ms/step - loss: 0.3797 - accuracy: 0.9292 - val_loss: 0.3337 - val_accuracy: 0.9500
Epoch 5/80
66/66 [==============================] - 3s 51ms/step - loss: 0.3179 - accuracy: 0.9531 - val_loss: 0.3173 - val_accuracy: 0.9400
Epoch 6/80
66/66 [==============================] - 3s 51ms/step - loss: 0.3460 - accuracy: 0.9173 - val_loss: 0.2872 - val_accuracy: 0.9500
Epoch 7/80
66/66 [==============================] - 3s 51ms/step - loss: 0.2492 - accuracy: 0.9714 - val_loss: 0.2717 - val_accuracy: 0.9444
Epoch 8/80
66/66 [==============================] - 3s 51ms/step - loss: 0.2404 - accuracy: 0.9645 - val_loss: 0.2328 - val_accuracy: 0.9711
Epoch 9/80
66/66 [==============================] - 3s 51ms/step - loss: 0.2135 - accuracy: 0.9726 - val_loss: 0.2225 - val_accuracy: 0.9689
Epoch 10/80
66/66 [==============================] - 3s 52ms/step - loss: 0.2099 - accuracy: 0.9749 - val_loss: 0.2571 - val_accuracy: 0.9656
```

Fig 13. Sample epochs: Inception V3

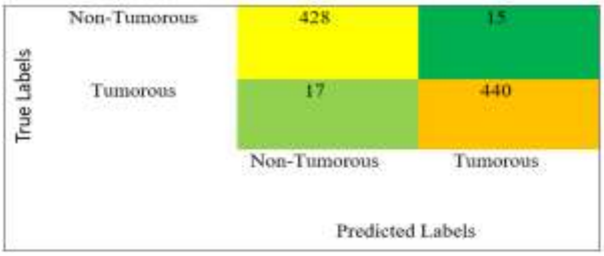

Fig 14. Confusion Matrix Inception V3

Table 4. Performance of Inception V3

TP	TN	FP	FN	Precision	Recall	F1 Score
440	428	15	17	96.70	96.28	0.96

The performance of Inception V3 is depicted in table 4.

6.3 Results of VGG-19

VGG-19, a shallow CNN architecture, was trained for 80 epochs with a batch size of 32 using sparse categorical cross-entropy as the loss function. The Adam optimizer with a very low learning rate of 0.01 was used to optimize the training. Few epochs are presented in figure 15. The confusion matrix produced after 80 epochs is shown in figure 16 below.

```
Epoch 1/80
66/66 [==============================] - 42s 495ms/step - loss: 0.7044 - accuracy: 0.5787 - val_loss: 0.5782 - val_accuracy: 0.5444
Epoch 2/80
66/66 [==============================] - 5s 76ms/step - loss: 0.5187 - accuracy: 0.7589 - val_loss: 0.4966 - val_accuracy: 0.8189
Epoch 3/80
66/66 [==============================] - 5s 76ms/step - loss: 0.3412 - accuracy: 0.8449 - val_loss: 0.3524 - val_accuracy: 0.8011
Epoch 4/80
66/66 [==============================] - 5s 76ms/step - loss: 0.2316 - accuracy: 0.9067 - val_loss: 0.2088 - val_accuracy: 0.9233
Epoch 5/80
66/66 [==============================] - 5s 76ms/step - loss: 0.1535 - accuracy: 0.9424 - val_loss: 0.1639 - val_accuracy: 0.9500
Epoch 6/80
66/66 [==============================] - 5s 76ms/step - loss: 0.1287 - accuracy: 0.9520 - val_loss: 0.2266 - val_accuracy: 0.9167
Epoch 7/80
66/66 [==============================] - 5s 76ms/step - loss: 0.1153 - accuracy: 0.9568 - val_loss: 0.2291 - val_accuracy: 0.9344
Epoch 8/80
66/66 [==============================] - 5s 76ms/step - loss: 0.1834 - accuracy: 0.9328 - val_loss: 0.1656 - val_accuracy: 0.9533
Epoch 9/80
66/66 [==============================] - 5s 76ms/step - loss: 0.1860 - accuracy: 0.9269 - val_loss: 0.1239 - val_accuracy: 0.9422
Epoch 10/80
66/66 [==============================] - 5s 75ms/step - loss: 0.1244 - accuracy: 0.9572 - val_loss: 0.1332 - val_accuracy: 0.9411
```

Fig 15. Sample epochs: VGG-19

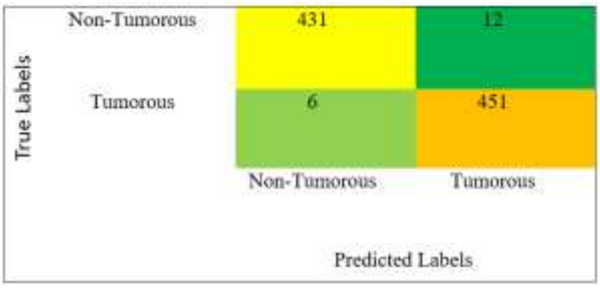

Fig 16. Confusion Matrix VGG-19

Table 5. Performance of VGG-19

TP	TN	FP	FN	Precision	Recall	F1 Score
451	431	12	6	97.40	98.68	0.98

The performance of VGG-19 is depicted in table 5.

6.4 Results of the proposed ensemble learning model

Ensemble learning is a technique that involves training multiple models on the same dataset and then combining their predictions. The fundamental objective of ensemble learning is to enhance performance by harnessing the collective knowledge of these models, thereby surpassing the capabilities of any individual model. Our proposed Ensemble Learning i.e. combining CNN, Inception V3 and VGG-19 performs well in the detection of brain tumors. The proposed method successfully detects several forms of brain tumors with good recall and precision which indicates a very low false positive rate. It achieved an impressive detection accuracy of 98% when applying the Transfer Learning approach with Ensemble Learning on the models. The results in table 6 showed the effectiveness of our proposed methodology.

Table 6. Results of the proposed ensemble learning model

Model	F1 Score	Precision	Recall	Accuracy
Ensemble Learning	0.98	98	98	98%

Finally, we carried out a comparison between our proposed model and other existing models which are shown in table 7.

Table 7. Performance comparison with existing works

Reference	Accuracy (%)
S. Beatrice et al [27]	96%
B Kokila et al [24]	92%
S. Patil et al [9]	90%
Proposed Ensemble Learning Model	**98%**

Hence, it can be affirmed that when dealing with a constrained dataset lacking an adequate number of images for neural network training, the application of transfer learning emerges as a valuable strategy to attain enhanced accuracy with a significantly reduced timeframe compared to training the model entirely from scratch.

7. Conclusion

In this work, we put forth a solution to the computer vision problem. The proposed model automates the detection of brain tumors in MRI images using Convolutional Neural Networks (CNNs) and transfer learning which in turn are integrated together using ensemble learning. The CNN architecture, Inception V3 and VGG-19 models used to extract features using transfer learning. Transfer learning introduces an innovative approach for analysing datasets with limited annotations by transferring knowledge from a source domain to a target domain. An accuracy of 98% achieved with majority voting count technique of Ensemble Learning on the experimental dataset. The comparison of results showed our model performed better than other existing models. In the future, this technique could be utilized to estimate tumor size, facilitating the determination of its stage. Furthermore, we recommend to apply this model to other tumor detection systems which suffers from lack of training data and where transfer learning can prove to be an effective and versatile solution.

References

1. H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty, A.B. M. Salem, “Classification using deep learning neural networks for brain tumors”, Future Computing and Informatics Journal 3 (2018) 68–71.
2. Chinta Someswararao “Brain Tumor Detection Model from MR Images using Convolutional Neural work”, 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), IEEE, 2020.
3. N. V. Shree, T. N. R. Kumar, “Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network”, Brain Informatics Journal 5 (2018) 23–30.
4. Hegde, R. B., Prasad, K., Hebbar, H., & Singh, B. M. K. (2019). Comparison of traditional image processing and deep learning approaches for classification of white blood cells in peripheral blood smear images. Biocybernetics and Biomedical Engineering, 39(2), 382-392.
5. Sarker, I.H., Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. SN Comput. Sci., 2, 420 (2021). https://doi.org/10.1007/s42979-021-00815-1
6. S. Das, O. F. M. R. R. Aranya, N. N. Labiba, “Brain tumor classification using convolutional neural network”, 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), IEEE, 2019.
7. H. Byale, G. Lingaraju, S. Sivasubramanian, “Automatic segmentation and classification of brain tumor using machine learning techniques”, International Journal of Applied Engineering Research, 13 (2018), 11686–11692.
8. Anandhanarayanan Kamalakannan, Yakub B, Govindaraj Rajamanickam, “Detection and Classification of Brain Tumor in MRI Images using Deep Convolutional Network”,2020 6th International Conference on Advanced Computing & Communication Systems (ICACCS), IEEE 2020.
9. S. Patil, D. Kirange, V. Nemade, “Predictive modelling of brain tumor detection using deep learning”, Journal of Critical Reviews 7 (04), (2020).

10. P. Kumar, B. Vijay Kumar, "Brain tumor MRI segmentation and classification using ensemble classifier", International Journal of Recent Technology and Engineering (IJRTE), 8, (2019).
11. Komal Sharma, Akwinder Kaur, Shruti Gujral, "Brain Tumor Detection based on Machined Learning Algorithms", International Journal of Computer Applications (IJCA), 103(1),2020
12. Bhagyashri H. Asodekar, Sonal A. Gore, A. D. Thakare, "Brain Tumor analysis Based on Shape Features of MRI using Machine Learning", 2019 5th International Conference On Computing, Communication, Control And Automation (ICCUBEA), IEEE, 2019.
13. Ranjeet Kaur, Amit Doegar, "Localization and Classification of Brain Tumor using Machine Learning & Deep Learning Techniques", International Journal of Innovative Technology and Exploring Engineering (IJITEE), 2019
14. A. Ari, D. Hanbay, "Deep learning based brain tumor classification and detection system", Turkish Journal of Electrical Engineering & Computer Sciences 26 (2018) 2275–2286.
15. T. L. Narayana, T. S. Reddy, "An efficient optimization technique to detect brain tumor from MRI images", 2018 International Conference on Smart Systems and Inventive Technology (ICSSIT), IEEE, 2018.
16. Iram Shahzadi, Tong Boon Tang, Fabrice Meriadeau, Abdul Quyyum, "CNN-LSTM: Cascaded Framework for Brain Tumour Classification", 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), IEEE 2018.
17. B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A. K. Singh, A. Elchouemi, "Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction", 6th International Conference on Smart Computing and Communications, ICSCC 2017, 7-8 December 2017, Kurukshetra, India.
18. M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, S. W. Baik, "Multigrade brain tumor classification using deep CNN with extensive data augmentation", Journal of computational science 30 (2019) 174–182.
19. A. Rajendran, R. Dhanasekaran, "Fuzzy Clustering and Deformable Model for Tumor Segmentation on MRI Brain Image: A Combined Approach," Procedia Engineering, Volume 30, 2012, Pages 327-333.
20. Hasnain Ali Shah, Faisal Saeed, Sangseok Yun, "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet", IEEE Access, 2022.
21. G. Hemanth, M.Janardhan, L.Sujihelen, "Design And Implementing Brain Tumor Detection Using Machine Learning Approach" , 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), IEEE 2019.
22. Dina Aboul Dahab, Samy S. A. Ghoniemy, Gamal M. Selim, "Automated Brain Tumor Detection and Identification using Image Processing and Probabilistic Neural Network Techniques", IJIPVC, Vol. 1, No. 2, pp. 1-8, 2012.
23. Song, Yantao & Ji, Zexuan & Sun, Quansen & Yuhui, Zheng. (2016). "A Novel Brain Tumor Segmentation from Multi-Modality MRI via A Level-Set-Based Model", Journal of Signal Processing Systems, 87, 249–257 (2017). https://doi.org/10.1007/s11265-016-1188-4.
24. B Kokila, M S Devadharshini, A Anitha, S Abishek Sankar, "Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images", Journal of Physics: Conference Series, Volume 1916, Issue 1, article id. 012226 (2021).
25. Ehab F. Badran, Esraa Galal Mahmoud, Nadder Hamdy, "An Algorithm for Detecting Brain Tumors in MRI Images", 2010 International Conference on Computer Engineering & Systems, IEEE, 2010.
26. Sanjay Kumar, J.N Singh, Inderpreet Kaur, "Brain Tumor MRI Image Segmentation and Noise Filtering Using FCNN", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Volume-9 Issue-5, March 2020.
27. S. Beatrice, Jay Yogesh Thanki, Tushar Ashok Dharia, Clive Jude D'Costa, "Brain Tumor Detection Using CNN", 2022 International Journal for Research in Applied Science & Engineering Technology (IJRASET).
28. https://www.kaggle.com/datasets/salikhussaini49/brain-image-clean/?select=train
29. Alzubaidi, L., Zhang, J., Humaidi, A.J. et al., "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions", Journal of Big Data 8, 53 (2021).
30. Muhammed Talo, Ozal Yildirim, Ulas Baran Baloglu, Galip Aydin, U Rajendra Acharya, "Convolutional neural networks for multi-class brain disease detection using MRI images", Computerized Medical Imaging and Graphics, Volume 78, 2019, 101673.